Change Detection For High-Resolution Satellite Images By Using Gaussian Mixture Model

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Abstract— In modern times, human civilization's settlement landscapes and patterns are changing rapidly because of the growth of human population, acceleration of urbanization and the application of varied technologies. Keep detecting and assessing these changes and mastering the accurate information are quite important for civilized human development. High resolution images provided by satellites are good resource to use to identify and quantify landscapes changes. We explore a detection method to identify landscape changes using high resolution satellite images. This grid based method is helpful in Bi-temporal change detection. By given two satellite images from the same area, it can identify changes accurately.

Keywords: Change Detection, Satellite Images, Gaussian Mixture Model

I. INTRODUCTION

Rapid urbanization has dramatically rebuilt the earth's landscape from its previous shape. Satellite images provide many valuable information about human settlements. Our objective in this study is to present an ongoing algorithmic research on change detection for high resolution satellite images. Change detection can be defined as the process of identifying differences in the state of an object or phenomenon by observing it at different times. There are different methods for the detection: Pixel-based method and Object-based method. On pixel level, change detection for high resolution satellite images is computationally expensive and sensitive to the geo-registration errors between images. High resolution satellite images are very elaborate, which causes objects cannot be presented by single pixel purely, each object is presented by multiple neighboring pixels with strong spatial correlation. The grid-based change detection, a sub-method of object-based, could reduce the computational cost and enhance the robustness to pixel level geo-registration errors by dividing the high-resolution images into grid blocks. The difference between temporal images can be quantified by using some distance measurements. There are various divergence and distance measures readily available from the literature. In our experiment we use Kullback-Leibler (KL) divergence since it has better performance than many other notable measures [1]. However, KL divergence is not a distance matrix and not scaled between 0 and 1, so we fit a Gaussian Mixture Model (GMM) to the KL divergence data, which is a good option since Gaussian Mixture Model has good property to model objects in grids.

II. RELATED WORK AND YOUR CONTRIBUTIONS

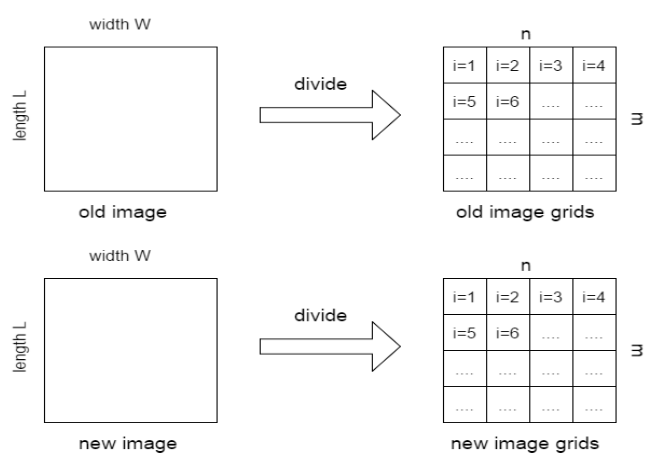
When using Pixel-based approach, the high resolution satellite images' changing detection, the computation will be expensive, and these images are sensitive to the geo-registration errors. High resolution satellite images are very elaborate, which causes objects cannot be presented by single pixel purely, each object is presented by multiple neighboring pixels with strong spatial correlation. We propose a Grid-based approach to identify changes which could reduce the computational cost and enhance the robustness to pixel level geo-registration errors by dividing the high-resolution images into grid blocks.

III. METHODOLOGY

To process the image data, we use the Python library including numpy and scipy as well as the OpenCV APIs, since every image can be decomposed into RGB values of real numbers. And the Gaussian Mixture Model algorithm is implemented in Python. For the human labeled images, we evaluate the results by the accuracy of change detection.

To divide the image into grids, we need to choose the right size of grids. The size of grids determines the quality and computational cost of the algorithm. It should not be too large since that may result in poor change detection: larger grids may contain more than a single object, therefore the Gaussian distribution fitted to the grid may not have a single peak. On the other hand, the time costs of computation will drastically reduce with increases in grid size. If the grid size is too small it would increase the computational cost, and may also cause model parameter estimation and matrix inversion problems. In our experiment, we use 140*140 pixel as the grid size.

We model the image data in each grid. Given two satellite images (one old and one new) which describe exactly the same land area, we divide these two images into two square grid clusters. The grids have the same size and each image has the same number of grids:



All multi-dimensional feature vectors from each pixel in the grid, are generated by a multi-variate Gaussian distribution described in the following equation:

$$P(x|y_i) = \frac{1}{\sqrt{(2\pi)^{-N}|\sum j|}} e^{-\frac{1}{2}(x-\mu j)^t|\Sigma j|^{-1}(x-\mu j)}$$

The standard multi-variate Gaussian distribution is described by the parameters mean (μ) and covariance matrix (Σ). These parameters are estimated for each grid separately from the corresponding image data.

For both image grid cluster, we convert each grid i into a Gaussian distribution.

$$P_{old}(i) \sim N(\mu_{ai}, \sigma_{ai}) \qquad Q_{new}(i) \sim N(\mu_{bi}, \sigma_{bi})$$

Then compute the Kullback–Leibler(KL) divergence between each pair of Gaussian distributions: (Here we use symmetric KL divergence to calculate the distance between $P_{old}(i)$ and $Q_{new}(i)$)

$$D_{KL}(i) = d(P_{old}(i), Q_{new}(i)) = KLdivergence\ d(P_{old}(i), Q_{new}(i))$$

With all $D_{KL}(i)$ we got after calculation, we can create a matrix map of KL divergence distance:

n

$D_{KL}(1)$	$D_{KL}(2)$	$D_{KL}(3)$	$D_{KL}(4)$
$D_{KL}(5)$	....	....	....
....	....	$D_{KL}(i)$	....
....	....	....	....

m

map of distance(KL)

Using the KL divergence matrix, we model this D_{KL} map into Gaussian Mixture Model: (Using EM algorithm to determine the parameters of Gaussian Mixture Model)

Assume $\{x_i = (r, c, R, G, B)\}_{i=1}^{n}$ generated by GMM

$$P(x_i|\Theta) = \sum_{j=1}^{k} \alpha_j N(x_i|\mu_j, \Sigma j)$$

E-step

$$P_{ij} = \frac{N(i,j)}{\sum_{l=1}^{k} N(i,l)}$$

M-step

$$\alpha_j = \frac{1}{n}\sum_{i=1}^{h} P_{ij} \qquad \mu_i = \frac{\sum_{i=1}^{n} x_i P_{ij}}{\sum_{i=1}^{n} P_{ij}} \qquad \Sigma j = \frac{\sum_{i=1}^{n}(x_i-\mu_j)P_{ij}(x_i-\mu_j)}{\sum_{i=1}^{n} P_{ij}}$$

(Converge and choose maximum α_j as cluster j)

Apply this clustering model to categorize the changes on KL divergence map, then we can plot the change map to detect changes.

IV. Experiments and Results

Initially we have two satellite images from the same area. Although these two images describe the same region of the land, the camera angle for these two are a little bit different (Figure 1).

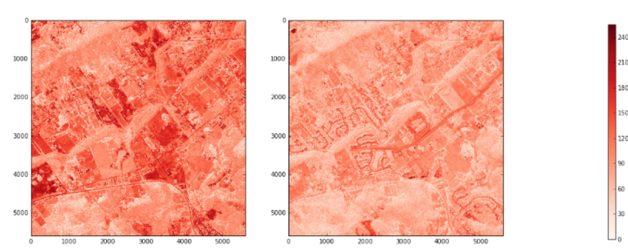
Figure 1

So before we start to use our detect method to these images, we need to do a pre-processing procedure for them. More specific, we should crop the black margins, and pick the maximum mutual rectangle area for both images with the same resolution. (Figure 2) After this, we can get two processed satellite images which are ready to be used for next step.

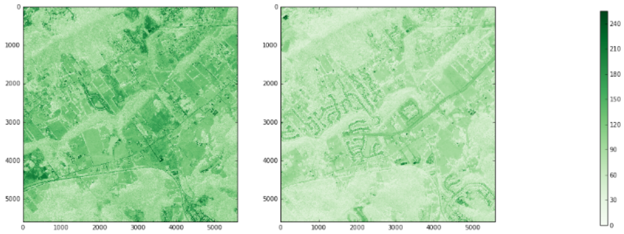
Figure 2

Before dividing these two images into grids, we noticed that there are many green color natural objects (trees, grasses, etc.) in both images. These massive amount of same color objects could affect the final detection result. To identify this kind of influence, we can transform the original images into different color's channels. In each channel, we compare the difference between the objects respectively.

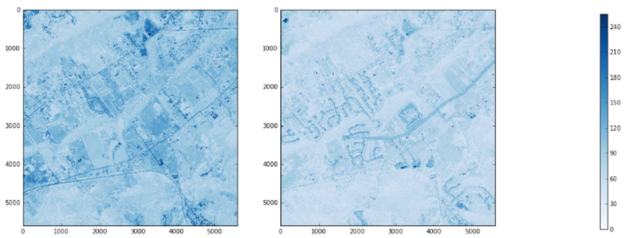
Images in red color channel:



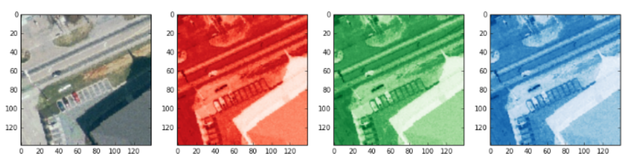
Images in green color channel:



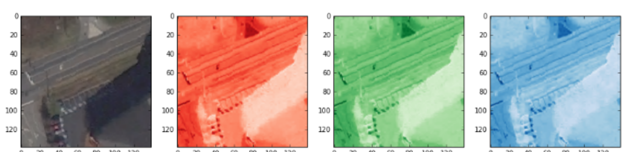
Images in blue color channel:



The next step is to divide the images into grids. For each image (with length l and width w), we divide image arrays into square grids based on preset grid size and scale RGB inside each grid. The example grids in original and RGB channels in older image as following:

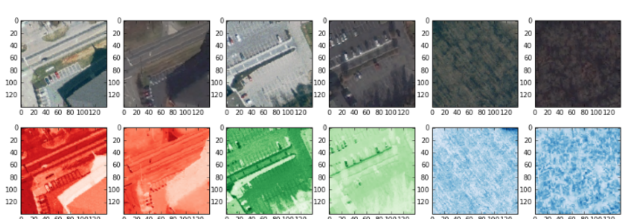


Relatively, the corresponding sample grids in these channels in newer images are:



The distinct difference between these two sets of samples are the building shadows. Which indicates the camera's orientation is changing, this could bring noise to our change detection. We can lower this affect by choosing the appropriate grid size.

Below are the extra sample grids in original image and express in single color channel:



Now we can transform the images. After dividing images into the grids properly, we convert all of these grids into their relative Gaussian distributions by using the RGB parameters. Then use these new distributions to compute the Kullback–Leibler (KL) divergence between Gaussian distribution pairs. As the result, we got a KL divergence map (Figure 3), which is critical to detect changes between the images.

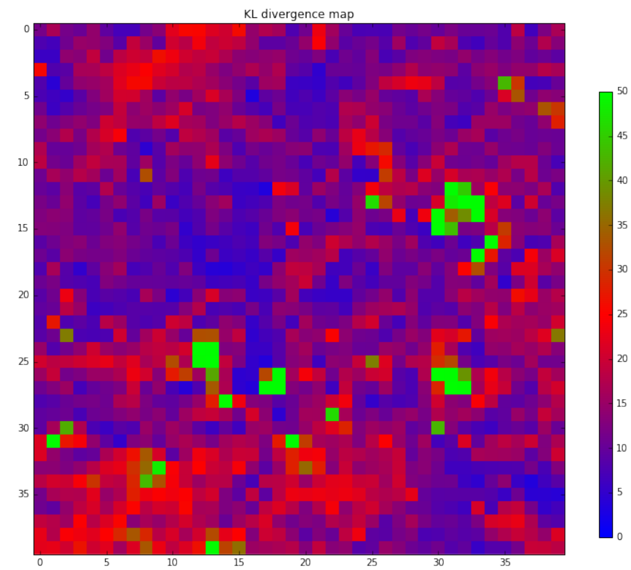


Figure 3

Using the KL divergence map, we can do a preliminary comparison overlaying this map on the original images (Figure 4):

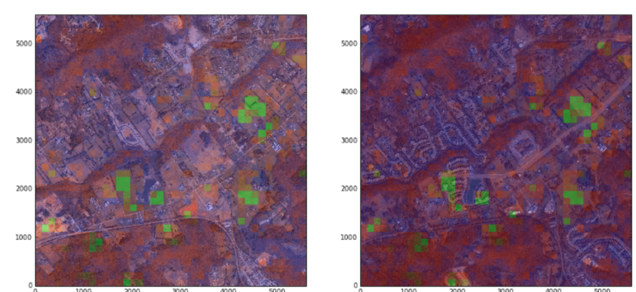


Figure 4

The green color square grids indicate some differences we detected by using our KL divergence map. However, the majority changing parts are still indistinctive. To solve this, we will adopt Gaussian Mixture Model to the map.

We build the GMM model-based clustering model by subset of KL divergence map, this GMM clustering model is able to categorize the changes on KL divergence map, then we can compare the difference between the two images by plotting the change map (Figure 5):

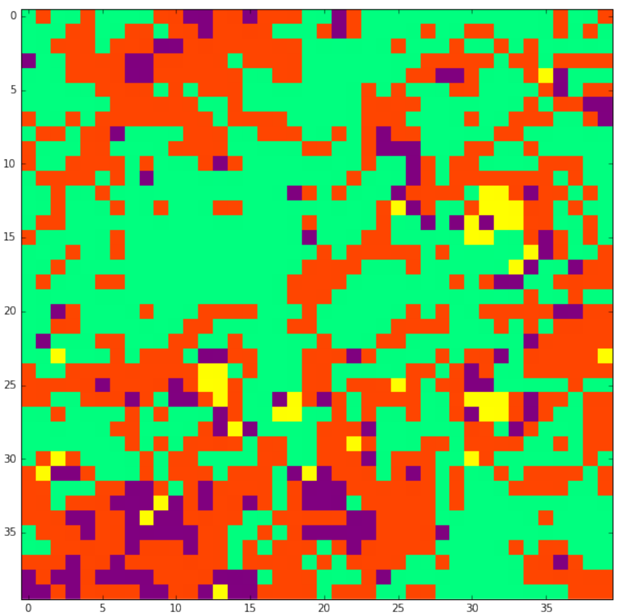


Figure 5

This is the final output from our method. As before, to compare the changes between two images more specific, we overlaid this GMM change cluster map onto the original satellite maps. (Figure 6) It will also be easier for us to evaluate the accuracy of our method.

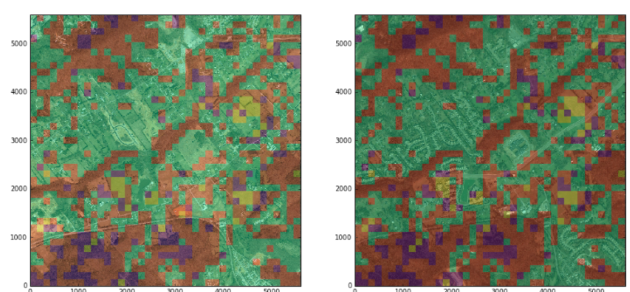
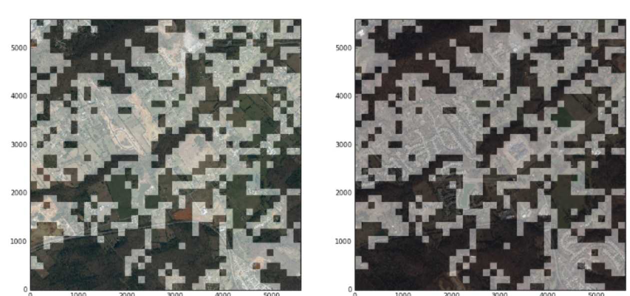


Figure 6

In the Figure 6, the green square grids suggest the areas have changes, all other parts are the areas that basically remain the same.

To highlight these significant changing areas, we reserve the most important changing parts (the green square grids), recolor them as white, and make all other square grids in the same dark color (Figure 7).



(Figure 7)

By observing these two original satellite images with human eyes, we could say that all major difference between two images are located in the white grids area. Particularly, those tree lines located at the central of images can be excluded perfectly from the changing parts. This is a very positive signal that suggests our method is useful for detecting the image changes. However, the final result map is not quite accurate to distinguish every detail of differences, and some minor changes are not detected by the change map. The potential reason of this may include the components k choosing, grids' size selecting, number of parameters using or some specific algorithm implementation problem.

To evaluate our result more specific, we use an external expert knowledge based changing map (Figure 8) as a reference.

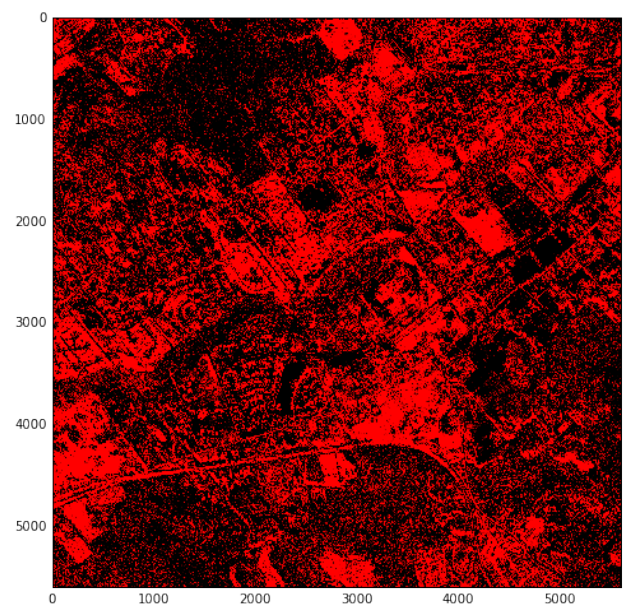


Figure 8

Divide this map into the same size grids as before, if the numbers of red pixels in each grid are above 30%, we consider this grid as "changed" (red), all other grids are treated as "unchanged" (black). Thus, we can get a labeled map to use for our evaluation (Figure 9).

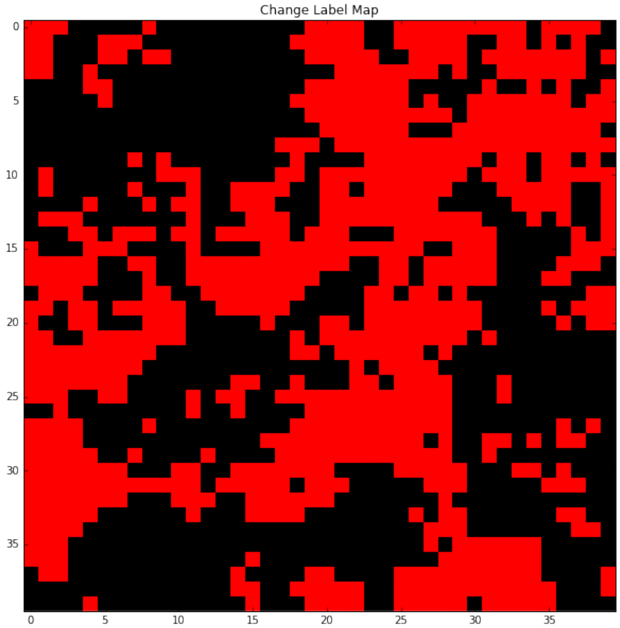


Figure 9

After overlaying this labeled map to our final output (Figure 10), we can see that the changed part in our output (white) are match to the labeled map (red) most of the time. Likewise, these two map's unchanged areas (black) are also similar.

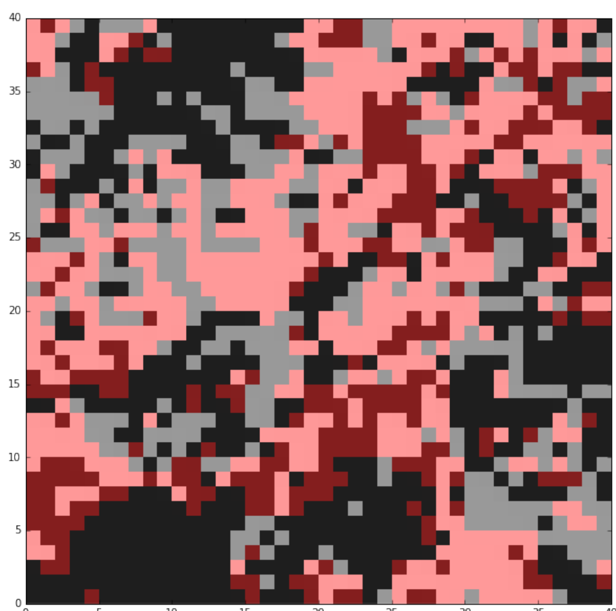


Figure 10

Now we are able to calculate the accuracy, precision, recall and F-measure between the output map (Figure 7) and the label map (Figure 9):

Accuracy: 0.629
Recall: 0.633
Precision: 0.604
F-measure: 0.618

The recall and precision values indicate that our model could detect the landscape change of new settlements in much agreement with the expert knowledge.

V. Conclusions and Future Directions

In our project, we presented a probabilistic change detection method. Although our method can detect the artificial changes between different satellite images to some extent, it still has quite parts to improve. Mostly the inaccuracy issue.

We attempted to use a method called Normalized Difference Vegetation Index (NDVI) when we tried to improve the accuracy. This is a unique technique to distinguish artificial buildings and vegetation with relative difference between R and G pixels. However, it did not perform well in our experiment (Figure 11), this is a potential direction in our future study.

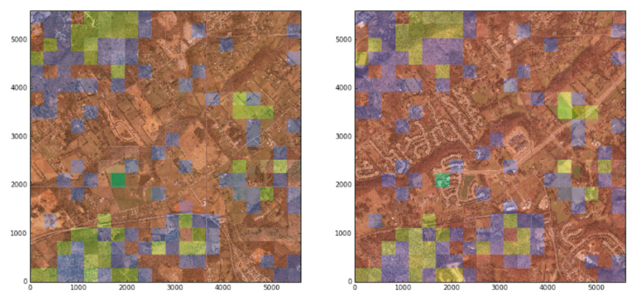


Figure 11

It's a challenging task for us to keep improving the performance of our method, but we believe after enough times' testing and adjusting, this method will have good prospects.

Acknowledgment

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